Chapter 5: Natural Language Processing as a Tool for Learning Analytics - Towards a Multi-Dimensional View of the Learning Process

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ABSTRACT

As educators turn to technology to supplement classroom instruction, the integration of natural language processing (NLP) into educational technologies is vital for increasing student success. NLP involves the use of computers to analyze and respond to human language, including students' responses to a variety of assignments and tasks. While NLP is widely used to deliver students with formative feedback, it can also be used to provide educators with information about task difficulty, students' individual differences, and student performance. In this chapter, we will first provide an overview of NLP, followed by a discussion of how NLP could be used to examine the learning process across a number of time points. Finally, we consider the future applications of NLP in the learning analytics domain.

Keywords: Linguistics, natural language processing, language, writing

Educational technologies are an increasingly popular supplement to classroom instruction, as they provide students with added opportunities for deliberate practice along with formative feedback. In many domains, these systems require students to input natural language in response to a variety of task demands, such as essays, reflective writing, metacognitive prompts, and even message board posts [17, 13]. For instance, AutoTutor [20] is an intelligent tutoring system (ITS) that trains students on science concepts through conversations in natural language. Similarly, iSTART [35] provides students with training on reading comprehension strategies by prompting students to self-explain difficult science texts.

These systems, along with many other educational technologies, rely on natural language processing (NLP) techniques to analyze and respond to students' responses. These responses can be in the form of explicit feedback messages delivered by the system; however, they can also be used to model information about the student (e.g., individual differences in knowledge or skills) as well as the task (e.g., the difficulty of the texts they are reading). For instance, Slater and colleagues [44] used NLP to examine how the different properties of mathematics word problems affected students' engagement with the ASSISTments tutoring system.

The integration of NLP into educational technologies is critical for increasing student learning in our globalized, digital world. In the rest of this chapter, we will first provide a broad overview of NLP, followed by an example of how NLP could be used to examine the learning process across a number of time points. We will then conclude with a description of the current and future applications of NLP in the learning analytics domain.

1 WHAT IS NATURAL LANGUAGE PROCESSING?

At its core, NLP is simply a methodology that relies on computers to automatically analyze human language [7]. The specific real-world applications of these analyses can range quite broadly, however, from the automatic translation of text from one language to another (e.g., Google Translate) to the development of virtual assistants or the classification of spam emails. Relevant to the field of learning analytics, NLP methodologies have a number of advantages over other methods of analyzing language data. In particular, because NLP does not rely on human raters, it can analyze large amounts of text data at surprisingly fast speeds. Impressively, NLP can also deal with both written text and speech data effectively. Thus, in handling large and often complex datasets, NLP is often recommended over human coding, as it offers both faster and less-biased analyses.

In considering how to use NLP to analyze linguistic data, it is important to consider the characteristics of human language. One of the key properties of language is that it is multi-dimensional and therefore constrained by both surface- and deep-level features [21, 43]. When using NLP methodologies, then, we must consider these various dimensions in our models containing linguistic content. In particular, we can automatically analyze texts along numerous dimension such as descriptive, lexical features, cohesion and semantic features [7, 10]. It is essential to capture the multi-dimensional aspect when analyzing linguistic data to create a clear picture of what the text really is – in essence, "The whole is better than sum of its parts." Below, we provide a brief overview of some of the most common dimensions of language that can be analyzed using NLP techniques.

1.1 Descriptive

NLP techniques can be used to calculate indices that relate to basic descriptive characteristics of a text, such as number of words, sentences, and paragraphs. Further, you can use these same techniques to calculate frequency counts at different levels of analyses – for instance, letters per word or words per sentence. Analyses such as these can be helpful for understanding a host of learning-related concepts, such as task completion or student engagement. For example, the average length of a student's forum posts in a MOOC has been shown to be a reliable predictor of whether that student will complete the online course [12, 11]. Descriptive NLP indices can also be essential for ensuring that students are given similar types of materials for practice or assessment purposes. For example, NLP techniques can be used to guide which texts or assignments to give students for homework or exams; by relying on descriptive features of the texts or assignments, the instructor or technology developer can have the power to control their materials by ensuring each text has similar features (i.e., they contain a similar number of words, paragraphs, etc.).

1.2 Lexical

The lexical properties of a text relate to characteristics of its words, such as their frequency in a given language (e.g., are the words common or rare?) and their concreteness (i.e., is the word more abstract or concrete?). These word-based features of language can be useful for understanding a host of information about educational materials and content [30]. For instance, NLP techniques can be used to calculate information about the degree to which a given text contains academic language, which can help with the classification of texts into genres or with the scoring of academic writing. Similarly, lexical indices can be used to calculate information about the readability of a given text – in other words, what age or grade level is a given text appropriate for? This information can then be used to help educators understand whether the language input is easy or difficult to read and if this difficulty level is appropriate for a specific population (e.g. 5th grade students or adult learners). Prior research indicates that information about word frequency can inform our understanding of text difficulty, with more frequently used words being easier for readers than less frequent words [24, 26]. Importantly, lexical information can be calculated by simply examining the individual words in a text. This therefore renders lexical indices particularly useful for examining a variety of text types regardless of their length, ranging from tweets or discussion posts [13] to reflective essays [17].

1.3 Syntax

Syntactic indices provide information about the structure of the sentences in a given text [31, 40]. One of the primary means through which individuals computationally analyze syntax in natural language is to measure its complexity – or, the ways in which discrete language units (e.g., words) can be combined to convey meaning [16]. Information about the complexity of syntactic structures can provide a wealth of insight into language, such as the quality of an essay or the readability of a text. Further, syntactic complexity measures have served as a powerful method for assessing the development of language, particularly in the case of second language learning (Ortega, 2003). Numerous indices can be calculated to describe the complexity of syntax in a given language, such as the mean length of clauses, mean length of t-units, or the number of words before the main verb. A number of writing studies have used these indices to discriminate between high- and low-skilled writers in both first and second language contexts [30]. Similarly, research has found syntactic complexity indices to be an indicator of text difficult, as more complex syntactic constructions tax the reader's working memory more heavily [19].

1.4 Cohesion

Cohesion measures provide information about the connections that are made between the ideas in a text. The presence of cohesion is beneficial for comprehension as it assists in coherence building [22]. For example, explaining causal relations in a text increase coherence, as using "because" connects two pieces of information and establishes a causal relation. Cohesion indices analyze these connections and provide a proxy for measuring coherence, examining how ideas are connected by looking at textual links between the sentences or the paragraphs. In education settings, measures of cohesion can provide insight into if students are making connections, which are important signs of comprehension.

1.5 Semantic Content

NLP techniques also provide information about the semantic content of the text. For example, the indices could reveal the main emphasis of the text and whether there is emotional or affective information. Additionally, if a text is written in response to another text, such as a summary or a source-based essay, NLP indices provide information about semantic overlap between texts. Semantic overlap is useful for educators because it provides insight into the students' understanding of a given text.

A multi-dimensional approach to analyzing language provides generous information about word and text level features, which can be used to analyzing many different types of language like tweets, discussion forums, essays or large documents. NLP also helps computers to communicate with humans in their own language and perform language-related tasks. Because of the language related benefits of NLP, it is an important tool for education. The information provided by NLP can assist educators in better understanding the problems students encounter across a variety of settings. For example, by looking at common mistakes, NLP can produce personalized feedback for improving writing. Additionally, such information can be provided quickly, making NLP very useful for effective formative feedback to students.

2 WHAT CAN NLP TELL US ABOUT LEARNING?

So far, we have provided an overview of NLP, particularly focusing on the multi-dimensional nature of language that can be captured with these techniques. It is important to then consider how these methodologies can be leveraged to provide critical information about the learning process. A large assumption of work in this domain is that the language of others can provide important data that can guide models in educational technologies, ranging from student-level variables (e.g., individual differences, performance) to task-level variables (e.g., difficulty). Thus, in utilizing NLP to analyze the language within their technologies, educational technology developers and researchers can better model the primary factors of the learning process. When this information is leveraged, we can provide more nuanced adaptive and personalized instruction and practice to students.

When considering how to best use NLP for learning analytics, the ideal methodology is to consider and analyze language across the multiple dimensions. This information can then be used to develop predictive models of student outcomes, allowing for targeted feedback and interventions. In the hands of educators, this provides a powerful instrument for individualized instruction. Importantly, these models must not only account for the multidimensional nature of language, but also the many stages at which language is involved in student learning. In light of these aims, we can consider three primary stages of analysis: input, process, and output. Below, we provide a brief overview of these stages along with examples of how NLP can be leveraged to improve models at each stage.

2.1 Input

Students are required to process language within educational contexts in a variety of forms, such as the texts they are asked to read, prompts to complete tasks, and questions that attempt to tap into their comprehension of the material. Further, they often receive information from their instructors and peers in the context of written language, particularly in the case of online platforms such as MOOCs.

Thus, one primary challenge that students face in online learning environments relates to their ability to understand the information they receive from these varied sources. For instance, an individual word or sentence may carry multiple meanings or require domain-specific prior knowledge. Therefore, the true meaning of the written language is implicit, leaving readers to make inferences in order to comprehend the text. NLP can provide insight into the different characteristics of the written language students are asked to process, as well as the impact of these features on student outcomes. These types of analyses can provide educators with important information about how they and their materials are impacting student achievement.

NLP can calculate features related to the readability of the text. A number of language features impact the overall readability of a given text, such as syntactic complexity, lexical sophistication, concreteness, genre, and cohesion [19, 21, 34]. Some of these features have an overarching impact. For example, the degree to which a text is narrative or expository impacts readability, with more narrative texts considered easier [24].

Additionally, reader factors can interact with text factors to impact learning. For example, readers' skill levels impact the text features that best support their learning. Increased levels of text cohesion have been shown to help readers with low prior knowledge, whereas decreased levels of text cohesion can help readers with high prior knowledge [34]. Reader engagement is also critical to learning outcomes. Linguistic features of math problems are related to student affect, which are associated with concentration and confusion [44]. These types of interactions can be helpful in improving the efficacy of educational technologies. For instance, if the system is able to understand the needs of the individual student, it can provide learning material that is most appropriate for that student to learn.

Knowledge about how text features interact with student outcomes has already been implemented within ITSs, such as iSTART [23, 34]. For example, iSTART adjusts the texts assigned to students to align with their vocabulary skills [35]. When a student has low vocabulary skills, iSTART will assign texts with more familiar and concrete words, compared to those assigned to peers with higher vocabulary skills. As student's vocabulary skills increase, iSTART can adapt and likewise increase the sophistication of the texts that students receive.

Analyzing the language students receive is one level at which NLP can be employed to improve student outcomes. In understanding the how the features of the text students interact with impacts learning, NLP can be used to adapt materials and enhance learning. However, NLP can be implemented at other levels to develop a clearer picture of student learning.

2.2 Process

Students' learning processes can also be modeled using features of their natural language input to educational technologies. For instance, students are often asked to type their thoughts during reading or while completing complex tasks. Researchers have long tapped into students' online processing and understanding by assessing the content of their verbal protocols or constructed responses to educational tasks. Verbal protocols ask students to report the content of their thoughts as they perform a task—providing insight into how they process information. In analyzing these verbal protocols, researchers have been able to explore and identify the cognitive mechanisms underlying various complex processes such as reading science texts or solving physics problems [14, 41, 42]. This methodology has allowed researchers to understand more about the strategies, processes, and knowledge involved in reading comprehension [36, 37].

One problem with these analyses is that they are often time-consuming and difficult for humans to conduct. Thus, NLP can help to automatically analyze students' verbal protocols, which can in turn provide critical insights into the meaning students construct during reading [5]. To illustrate, consider the way in which students comprehend complex science texts. Research suggests that text comprehension relies on an individual to construct a mental representation of the text. To achieve this, readers rely on their knowledge of language and domain of the text content, as well as reading skills and strategies [27, 36]. This includes generating connections among the concepts in the text and prior knowledge, which establishes coherence and promotes deep comprehension [28]. The overall coherence of a reader's mental representation is positively associated with the degree to which readers active and use prior knowledge, to develop these connections amongst information [36]. This is supported by evidence that skilled and knowledgeable readers are more likely to generate such connections [38, 39].

The use of NLP to examine reader's think aloud responses have provided insight into the processes involved in the development of a coherent mental representation of the text. For example, the level of cohesion, or explicit cues in a text that signal readers to make connections among ideas, can be used as a proxy for coherence [9, 25]. The presence of connectives in a reader's constructed response can indicate that they are making connections between information as they read. Additionally, the type and amount of cohesion (assessed through NLP) can provide insight into the processes in which students engage to achieve comprehension. For example, Allen et al. [1] found that when readers engaged in deep comprehension through self-explanation training, readers' constructed responses were less lexically cohesive, but more causally and semantically cohesive.

Some ITSs implement NLP to analyze students' verbal protocols to gain insight into students' understanding of particular concepts and formulate targeted feedback. For example, AutoTutor [20] uses NLP to analyze tutor dialogues to assess student understanding and provide appropriate feedback. Likewise, the Reading Strategy Assessment Tool [18] prompts students to answer two types of open-ended questions during reading: direct and indirect questions. Direct questions ask students about the content of the text, and analysis of student answers provide insight into comprehension. Indirect questions ask students about their thoughts during reading, which taps into comprehension processes that students employ. Analysis of these answers reveal students' use of paraphrasing, bridging, and elaboration strategies that support comprehension [32]. Students benefit from this individualized instruction and adaptive content.

2.3 Output

Finally, students' produce language as output that can take many forms, such as a short-answer, message board response, or essays. NLP methodologies can be used to analyze these student responses, and further contribute to modeling student learning and achievement outcomes.

For example, a large body of research has looked at using NLP to analyze student writing and develop automated essay scoring (AES) engines. These engines are designed to model expert human raters and provide fast, quality feedback on student writing. Using AES techniques, NLP can be integrated into current writing instruction and improve student's writing skills [29]. Additionally, feedback need not be surface level detail but can also encompass high-level feedback such as structure and organization [15, 46]. Modeling how students present and connect topics in an essay can generate feedback to help students elaborate on underdeveloped ideas, reduce redundancy, and improve essay coherence [46]. Multi-dimensional analysis through neural sequence modeling of student writing can likewise provide instant feedback on essay structure and actionable steps for essay modification [15]. Such feedback is highly personalized to the student and provides a powerful tool for educators to recognize patterns in student's understanding.

Work in developing these engines have revealed the linguistic features of high-quality writing. For example, essays are considered high-quality when they contain more diverse and sophisticated word choices and more complex syntax [9]. Notably, features of high-quality student essays are not the same as high-quality texts. While syntactic complexity is related to higher ratings of essay quality, texts that contain more syntactic complexity have been shown to increase working memory load and decrease comprehension [19].

Additionally, features of students' essay writing, as assessed by NLP, can also reveal individual differences. For example, lexical properties of student essays have been used to predict student vocabulary knowledge [3]. Modeling students' individual differences can give educators insight into students' strengths and weaknesses, providing additional opportunities for specific and personalized instruction.

In considering not only the multidimensional nature of language, but also the multiple dimensions across which language is utilized in learning, models can become a powerful educational device. Educators can learn how, and for whom, to adapt their materials to promote better learning outcomes. Students' online processing of materials can trigger adaptive feedback to prevent misunderstanding. Students' learning outcomes can be used to predict course performance, and prompt tailored assistance. Students' continued interaction with the system continuously updates the model, representing more personalized instruction based on students' knowledge and performance.

3 WHERE ARE WE HEADED?

The use of linguistic data in learning analytics allows for a more comprehensive view of the educational experience. To this end, we suggest that the strongest potential avenues for research in this area are multimodal in nature. In particular, we suggest researchers focus on methodologies that allow for the integration of NLP analyses with the expansive work that is already being conducted in the field.

One example of this multimodal integration is found in work that emphasizes the dynamic nature of language production processes [2]. Education and cognitive science researchers, for instance, have relied heavily on reading times and eye-tracking to provide information about students' cognitive processes while engaging with educational materials [26, 33, 47]. Although researchers have made a significant effort to leverage these methodologies, there has been a significantly smaller amount of research conducted on students' online language production processes [45].

Thus, one area for future research lies in the temporal tracking of the keystrokes produced by students while writing [6, 45]. NLP analyses generally focus on the final written product; however, keystroke analyses focus on the writing process by examining the keys that are pressed while writing, and in particular, the timing of the keystrokes as well as the backspaces that are invisible within the final product. Recently, tools have been developed to facilitate recording the individual keystrokes pressed by individuals during writing [1, 8, 45].

Bixler and D'Mello (2013) provided preliminary results supporting the promise of keystroke analyses in the detection of affective states. They found that a combination of keystroke and individual difference measures (i.e., scholastic aptitude, writing apprehension, and exposure to print) afforded the diagnosis of self-reported affective states (i.e., neutral, boredom, engagement) during writing with accuracies of 11% to 38% above baseline. Similarly, Allen et al. [4] predicted engagement and boredom across multiple writing sessions using a combination of academic ability (e.g., scholastic aptitude), linguistic text properties, and keystroke indices. The combination of these indices achieved an accuracy of 77% in classifying high and low engagement and boredom in writing sessions.

These studies represent initial explorations of writing using online keystroke analyses. Many more questions on the contributions of various factors can be explored using this approach. Consider, perhaps as a more real-world example, pausing to search the internet for a word, a concept, or to check the correct syntax for a particular phrase. What are these processes and how can we use information about them to understand writing? How can an integration of technologies, such as keystroke logging and NLP inform writing theories? Our strong sense is that pursuing answers to these (and other) questions will help to inspire theories of the cognitive and sociocultural processes that drive writing performance.

4 CONCLUSION

The purpose of this chapter was to provide a brief overview of NLP techniques and methodologies, and to propose new areas of research that leverage NLP within the learning analytics domain. In this chapter, we have pointed toward several directions that we consider particularly fruitful. However, any number of directions might be taken to establish a more comprehensive understanding of writing. We have also made an explicit argument for the integration of NLP into broader work in learning analytics. Research on the linguistic aspects of natural language has largely been conducted separately from learning analytics research. One objective here is to encourage researchers in the learning analytics community to extend their research to the study of language, and to encourage researchers to draw on literature from this community to help move our research forward. We believe that such an approach is essential to developing a more well-rounded view of the learning process.

REFERENCES

[1] Laura K. Allen, Matthew E. Jacovina, and Danielle S. McNamara. "Cohesive features of deep text comprehension processes". In: 2016. URL: https://eric.ed.gov/?id=ED577140 (visited on 04/24/2020).

[2] Laura K. Allen, Aaron D. Likens, and Danielle S. McNamara. "Writing flexibility in argumentative essays: a multidimensional analysis". In: *Reading and Writing* 32.6 (June 1, 2019), pp. 1607–1634. ISSN: 1573-0905. DOI: 10.1007/s11145-018-9921-y. URL: https://doi.org/10.1007/s11145-018-9921-y.

[3] Laura K. Allen and Danielle S. McNamara. "You are your words: Modeling students' vocabulary knowledge with natural language processing tools". In: International Educational Data Mining Society, June 2015. URL: https://eric.ed.gov/?id=ED560539 (visited on 04/24/2020).

[4] Laura K. Allen, Caitlin Mills, Matthew E. Jacovina, Scott Crossley, Sidney D'Mello, and Danielle S. McNamara. "Investigating boredom and Engagement during writing using multiple sources of information: The essay, the writer, and keystrokes". In: *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*. LAK '16. New York, NY, USA: Association for Computing Machin-

ery, 2016, pp. 114–123. ISBN: 978-1-4503-4190-5. DOI: 10.1145/2883851.2883939. URL: https://doi.org/10.1145/2883851.2883939.

[5] Laura K. Allen, Caitlin Mills, Matthew E. Jacovina, Scott Crossley, Sidney D'Mello, and Danielle S. McNamara. "Investigating boredom and engagement during writing using multiple sources of information: The essay, the writer, and keystrokes". In: *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*. LAK '16. New York, NY, USA: Association for Computing Machinery, 2016, pp. 114–123. ISBN: 978-1-4503-4190-5. DOI: 10.1145/2883851.2883939. URL: https://doi.org/10.1145/2883851.2883939.

[6] Huub van den Bergh and Gert Rijlaarsdam. "Chapter 9: The Dynamics of Idea Generation During Writing: An Online Study". In: *Writing and Cognition*. Jan. 1, 2007, pp. 125–150. URL: https://brill.com/view/book/edcoll/9781849508223/B9781849508223-s010.xml (visited on 04/24/2020).

[7] Steven Bird, Ewan Klein, and Edward Loper. *Natural language processing with Python: Analyzing text with the natural language toolkit*. " O'Reilly Media, Inc.", 2009.

[8] Robert Bixler and Sidney D'Mello. "Towards automated detection and regulation of affective states during academic writing". In: *Artificial Intelligence in Education*. Ed. by H. Chad Lane, Kalina Yacef, Jack Mostow, and Philip Pavlik. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 904–907. ISBN: 978-3-642-39112-5.

[9] Scott Crossley and Danielle McNamara. "Text coherence and judgments of essay quality: Models of quality and coherence". In: *Proceedings of the Annual Meeting of the Cognitive Science Society*. Vol. 33. 2011.

[10] Scott A. Crossley, Laura K. Allen, and Danielle S. McNamara. "A multi-dimensional analysis of essay writing". In: *Multi-Dimensional Analysis* 25 (2014), pp. 197–237.

[11] Scott A. Crossley, Mihai Dascalu, Danielle S. McNamara, Ryan Baker, and Stefan Trausan-Matu. "Predicting success in massive open online courses (MOOCs) using cohesion network analysis". In: Philadelphia, PA: International Society of the Learning Sciences., 2017.

[12] Scott A. Crossley, Danielle S. McNamara, Ryan Baker, Yuan Wang, Luc Paquette, Tiffany Barnes, and Yoav Bergner. "Language to completion: Success in an educational data mining Massive Open Online Class". In: International Educational Data Mining Society, June 2015. URL: https://eric.ed.gov/?id=ED560771 (visited on 04/24/2020).

[13] Nia Dowell and Vitomir Kovanović. "Modeling Educational Discourse with Natural Language Processing". In: *The Handbook of Learning Analytics*. Ed. by Charles Lang, Alyssa Friend Wise, Agathe Merceron, Dragan Gašević, and George Siemens. 2nd ed. Vancouver, Canada: SOLAR, 2022. ISBN: 978-0-9952408-3-4. URL: https://www.solaresearch.org/publications/hla-22/.

[14] K. Anders Ericsson and Herbert A. Simon. *Protocol analysis: Verbal reports as data*. the MIT Press, 1984.

[15] James Fiacco, Elena Cotos, and Carolyn Rosé. "Towards enabling feedback on rhetorical structure with neural sequence models". In: *Proceedings of the 9th International Conference on Learning Analytics & Knowledge - LAK19*. the 9th International Conference. Tempe, AZ, USA: ACM Press, 2019, pp. 310–319. ISBN: 978-1-4503-6256-6. DOI: 10.1145/3303772.3303808. URL: http://dl.acm.org/citation.cfm?doid=3303772.3303808 (visited on 04/24/2020).

[16] V. Fromkin, R. Rodman, and N. Hyams. *An Introduction to Language*. Cengage Learning, 2013.

[17] Andrew Gibson and Antonette Shibani. "NLP - Writing Analytics". In: *The Handbook of Learning Analytics*. Ed. by Charles Lang, Alyssa Friend Wise, Agathe Merceron, Dragan Gašević, and George Siemens. 2nd ed. Vancouver, Canada: SOLAR, 2022. ISBN: 978-0-9952408-3-4. URL: https://www.solaresearch.org/publications/hla-22/.

[18] Sara Gilliam, Joseph P. Magliano, Keith K. Millis, Irwin Levinstein, and Chutima Boonthum. "Assessing the format of the presentation of text in developing a Reading Strategy Assessment Tool (R-SAT)". In: *Behavior Research Methods* 39.2 (May 2007), pp. 199–204. ISSN: 1554-351X, 1554-3528. DOI: 10.3758/BF03193148. URL: http://link.springer.com/10.3758/BF03193148 (visited on 04/24/2020).

[19] Arthur C. Graesser, Zhiqiang Cai, Max M. Louwerse, and Frances Daniel. "Question Understanding Aid (QUAID) a web facility that tests question comprehensibility". In: *Public Opinion Quarterly* 70.1 (2006), pp. 3–22.

[20] Arthur C. Graesser, Shulan Lu, George Tanner Jackson, Heather Hite Mitchell, Mathew Ventura, Andrew Olney, and Max M. Louwerse. "AutoTutor: A tutor with dialogue in natural language". In: *Behavior Research Methods, Instruments, & Computers* 36.2 (May 2004), pp. 180–192. ISSN: 0743-3808, 1532-5970. DOI: 10.3758/BF03195563. URL: http://link.springer.com/10.3758/BF03195563 (visited on 04/24/2020).

[21] Arthur C. Graesser, Danielle S. McNamara, and Jonna M. Kulikowich. "Coh-Metrix: Providing multilevel analyses of text characteristics". In: *Educational Researcher* 40.5 (June 1, 2011), pp. 223–234. ISSN: 0013-189X. DOI: 10.3102/

0013189X11413260. URL: https://doi.org/10.3102/0013189X11413260 (visited on 04/24/2020).

[22] Arthur C. Graesser, Danielle S. McNamara, and Max M. Louwerse. "What do readers need to learn in order to process coherence relations in narrative and expository text". In: *Rethinking reading comprehension* (2003), pp. 82–98.

[23] Arthur C. Graesser, Danielle S. McNamara, and Kurt VanLehn. "Scaffolding Deep Comprehension Strategies Through Point&Query, AutoTutor, and iSTART". In: *Educational Psychologist* 40.4 (Dec. 2005), pp. 225–234. ISSN: 0046-1520, 1532-6985. DOI: 10.1207/s15326985ep4004_4. URL: http://www.tandfonline.com/doi/abs/10.1207/s15326985ep4004_4 (visited on 04/24/2020).

[24] Karl F. Haberlandt and Arthur C. Graesser. "Component processes in text comprehension and some of their interactions". In: *Journal of Experimental Psychology: General* 114.3 (1985), pp. 357–374.

[25] M. A. K. Halliday and Ruqaiya Hasan. *Grammatical Cohesion in Spoken and Written English*. Londres, Logman, 1978.

[26] Marcel A. Just and Patricia A. Carpenter. "A theory of reading: From eye fixations to comprehension". In: *Psychological review* 87.4 (1980), pp. 329–354. DOI: 10.1037/0033-295X.87.4.329.

[27] Walter Kintsch. "The role of knowledge in discourse comprehension: A construction-integration model". In: *Psychological review* 95.2 (1988), pp. 163–182. DOI: 10.1037/0033-295X.95.2.163.

[28] Walter Kintsch and Teun A. van Dijk. "Toward a model of text comprehension and production". In: *Psychological Review* 85.5 (1978), pp. 363–394. ISSN: 0033-295X. DOI: 10.1037/0033-295X.85.5.363. URL: http://content.apa.org/journals/rev/85/5/363 (visited on 04/24/2020).

[29] Simon Knight, Antonette Shibani, and Simon Buckingham-Shum. "Augmenting formative writing assessment with learning analytics: A design abstraction approach". In: International Society of the Learning Sciences, Inc.[ISLS]., 2018.

[30] Kristopher Kyle and Scott A. Crossley. "Measuring syntactic complexity in L2 writing using fine-grained clausal and phrasal indices". In: *The Modern Language Journal* 102.2 (June 1, 2018), pp. 333–349. DOI: 10.1111/modl.12468. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/modl.12468 (visited on 05/06/2020).

[31] Xiaofei Lu. "A corpus-based evaluation of syntactic complexity measures as indices of college-level ESL writers' language development". In: *TESOL quarterly* 45.1 (2011), pp. 36–62.

[32] Joseph P. Magliano, Keith K. Millis, and Irwin Levinstein. "Assessing comprehension during reading with the Reading Strategy Assessment Tool (RSAT)". In: *Metacognition and learning* 6.2 (Aug. 2011), pp. 131–154. ISSN: 1556-1623. DOI: 10.1007/s11409-010-9064-2. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3725311/ (visited on 05/03/2020).

[33] Scott A. McDonald, R. H. S. Carpenter, and Richard C. Shillcock. "An anatomically constrained, stochastic model of eye movement control in reading". In: *Psychological Review* 112.4 (2005), pp. 814–840. DOI: 10.1037/0033-295X.112.4.814.

[34] Danielle S. McNamara, Eileen Kintsch, Nancy Butler Songer, and Walter Kintsch. "Are good texts always better? Interactions of text coherence, background knowledge, and levels of understanding in learning from text". In: *Cognition and instruction* 14.1 (1996), pp. 1–43.

[35] Danielle S. McNamara, Irwin B. Levinstein, and Chutima Boonthum. "iSTART: Interactive strategy training for active reading and thinking". In: *Behavior Research Methods, Instruments, & Computers* 36.2 (May 2004), pp. 222–233. ISSN: 0743-3808, 1532-5970. DOI: 10.3758/BF03195567. URL: http://link.springer.com/10.3758/BF03195567 (visited on 04/24/2020).

[36] Danielle S. McNamara and Joe Magliano. "Chapter 9 Toward a Comprehensive Model of Comprehension". In: *Psychology of Learning and Motivation*. Vol. 51. Academic Press, Jan. 1, 2009, pp. 297–384. URL: http://www.sciencedirect.com/science/article/pii/S0079742109510092.

[37] Keith Millis and Joseph Magliano. "Assessing comprehension processes during reading". In: *Reaching an understanding* (2012), pp. 35–54.

[38] Keith Millis, Joseph Magliano, and Stacey Todaro. "Measuring discourse-level processes with verbal protocols and latent semantic analysis". In: *Scientific Studies of Reading* 10.3 (2006), pp. 225–240.

[39] Jane Oakhill and N. Yuill. "Pronoun resolution in skilled and less-skilled comprehenders: Effects of memory load and inferential complexity". In: *Language and Speech* 29.1 (1986), pp. 25–37. DOI: 10.1177/002383098602900104.

[40] Lourdes Ortega. "Syntactic complexity measures and their relationship to L2 proficiency: A research synthesis of college-level L2 writing". In: *Applied linguistics* 24.4 (2003), pp. 492–518.

[41] Yasuhiro Ozuru, Kyle Dempsey, and Danielle S. McNamara. "Prior knowledge, reading skill, and text cohesion in the comprehension of science texts". In: *Learning and Instruction* 19.3 (June 2009), pp. 228–242. ISSN: 09594752. DOI: 10.1016/j.learninstruc.2008.04.003. URL: https://linkinghub.elsevier.com/retrieve/pii/S0959475208000534 (visited on 04/24/2020).

[42] Michael Pressley and Peter Afflerbach. *Verbal protocols of reading: The nature of constructively responsive reading*. Lawrence Erlbaum Associates, Inc., 1995.

[43] Tony Berber Sardinha and Marcia Veirano Pinto. *Multi-Dimensional Analysis, 25 Years On: A tribute to Douglas Biber*. John Benjamins Publishing Company, July 15, 2014. 368 pp. ISBN: 978-90-272-7015-3.

[44] Stefan Slater, Jaclyn Ocumpaugh, Ryan Baker, Ma Victoria Almeda, Laura Allen, and Neil Heffernan. "Using natural language processing tools to develop complex models of student engagement". In: *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE, 2017, pp. 542–547.

[45] Luuk Van Waes, Mariëlle Leijten, Eva Lindgren, and Å Wengelin. "Keystroke logging in writing research: Analyzing online writing processes." In: *Handbook of writing research*. The Guilford Press, 2016, pp. 410–426.

[46] Jovita M. Vytasek, Alexandra Patzak, and Philip H. Winne. "Topic development to support revision feedback". In: *Proceedings of the 9th International Conference on Learning Analytics & Knowledge - LAK19*. the 9th International Conference. Tempe, AZ, USA: ACM Press, 2019, pp. 220–224. ISBN: 978-1-4503-6256-6. DOI: 10.1145/3303772.3303816. URL: http://dl.acm.org/citation.cfm?doid=3303772.3303816 (visited on 04/24/2020).

[47] Shunnan Yang and George W. McConkie. "Eye movements during reading: A theory of saccade initiation times". In: *Vision Research* 41.25 (2001), pp. 3567–3585. DOI: 10.1016/S0042-6989(01)00025-6.